SENTIMENT ANALYSIS OF TWEETS ON APPLE AND GOOGLE

A Machine Learning Approach to Brand Emotion Tracking

Group 3

PROJECT OVERVIEW

- **Objective**: Classify sentiments in tweets about Apple and Google products.
- **Use Case**: Help brands monitor public perception and guide marketing decisions.
- **Dataset**: 9,000+ tweets labeled as Positive, Negative, Neutral, or No Emotion.

WHY THIS MATTERS

- Tweets are modern-day customer reviews.
- Brands need to act fast on public sentiment.
- Understanding the "emotional pulse" of users drives smarter campaigns.

THE PROBLEM STATEMENT

"What do people really feel when they tweet about Apple or Google products?"

Customers express feelings subtly and sometimes sarcastically.

- Brands want to:
- Understand real-time feedback.
- Improve product features.
- Manage brand reputation.

NLP- PREPROCESSING

"Turning Twitter slang into data gold"

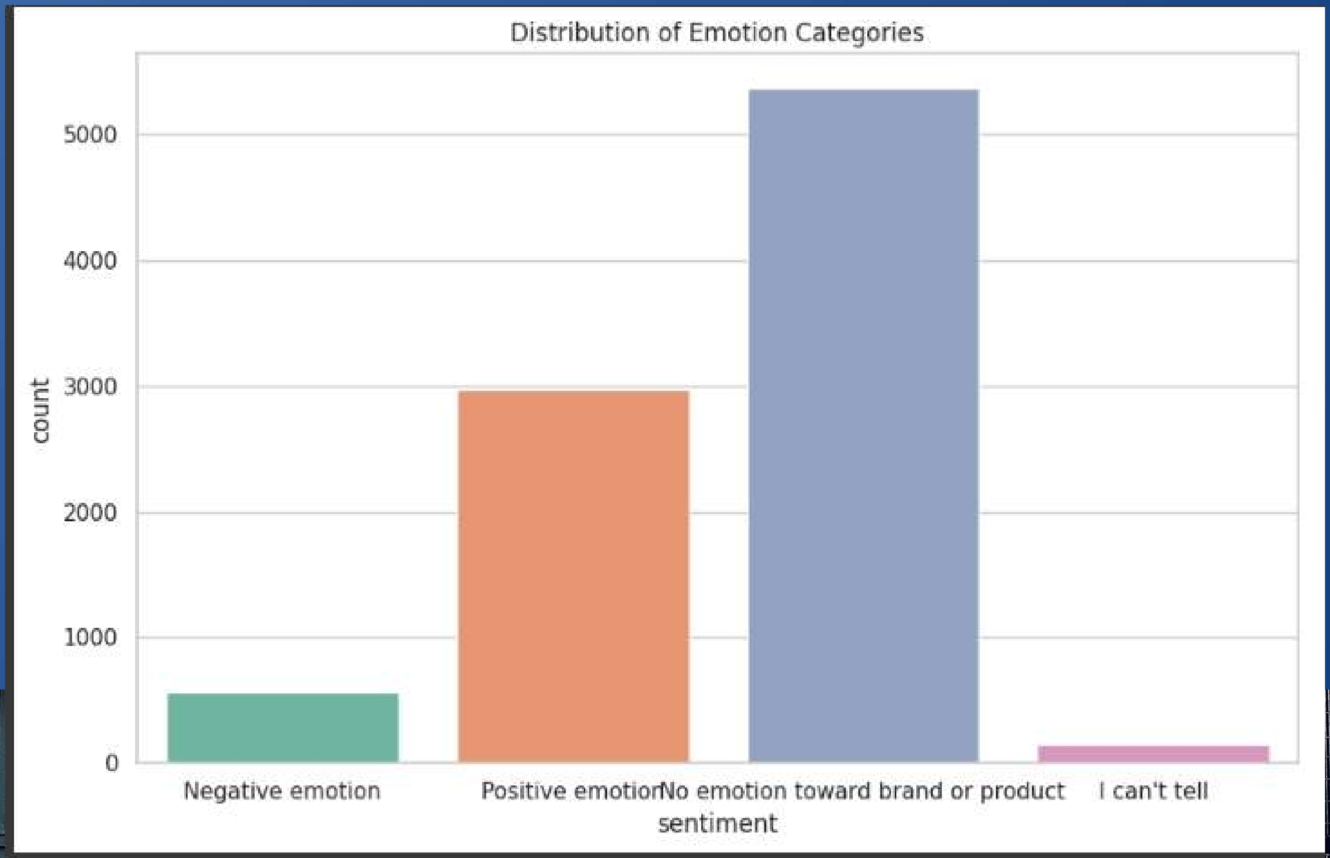
- **Tokenization:** We used word_tokenize() from NLTK to accurately split tweets into individual words, handling punctuation and slang effectively.
- **Stopword Removal:** Common words like "the", "is", and "and" were filtered using NLTK's stopwords, ensuring the model focuses on emotionally charged and meaningful words.
- **Lemmatization:** Using NLTK's WordNetLemmatizer, we reduced words to their base forms (e.g., "running" to "run") for better generalization without distorting sentiment context.
- Combined, these NLP techniques helped clean noisy, informal tweet text into a structured format suitable for machine learning.

CLEANING THE NOISE

```
Original Tweet: RT @mention Before It Even Begins, Apple WinsåÊ#SxSW, {link} -> gonna get sum! via @mention
Cleaned Tweet: rt even begin apple win sxsw link gt gon na get sum via

Original Tweet: Makeshift apple store at 6th and congress. You're kidding me. Amazing #sxsw #apple
Cleaned Tweet: makeshift apple store th congress kidding amazing sxsw apple

Original Tweet: Just downloaded an ipad app for countering jetlag in Austin. #sxsw
Cleaned Tweet: downloaded ipad app countering jetlag austin sxsw

Original Tweet: Class starts now. #SXSW @mention Designing iPad Interfaces - New Navigation Schemas {link}
Cleaned Tweet: class start sxsw designing ipad interface new navigation schema link

Original Tweet: RT @mention Win free iPad 2 from webdoc.com #sxsw RT
Cleaned Tweet: rt win free ipad webdoc com sxsw rt
```

DATA EXPLORATION

Positive sentiment is more frequent than negative, but underrepresented in some products.



WORD CLOUDS TELL A STORY

FEATURE ENGINEERING

"We taught the computer what to look for"

- Used TF-IDF (Term Frequency-Inverse Document Frequency).
- Bigrams included for better phrase understanding.
- Labels encoded: 0 to 3 based on sentiment.

LSTM

The Smart Student Who Froze in the Exam

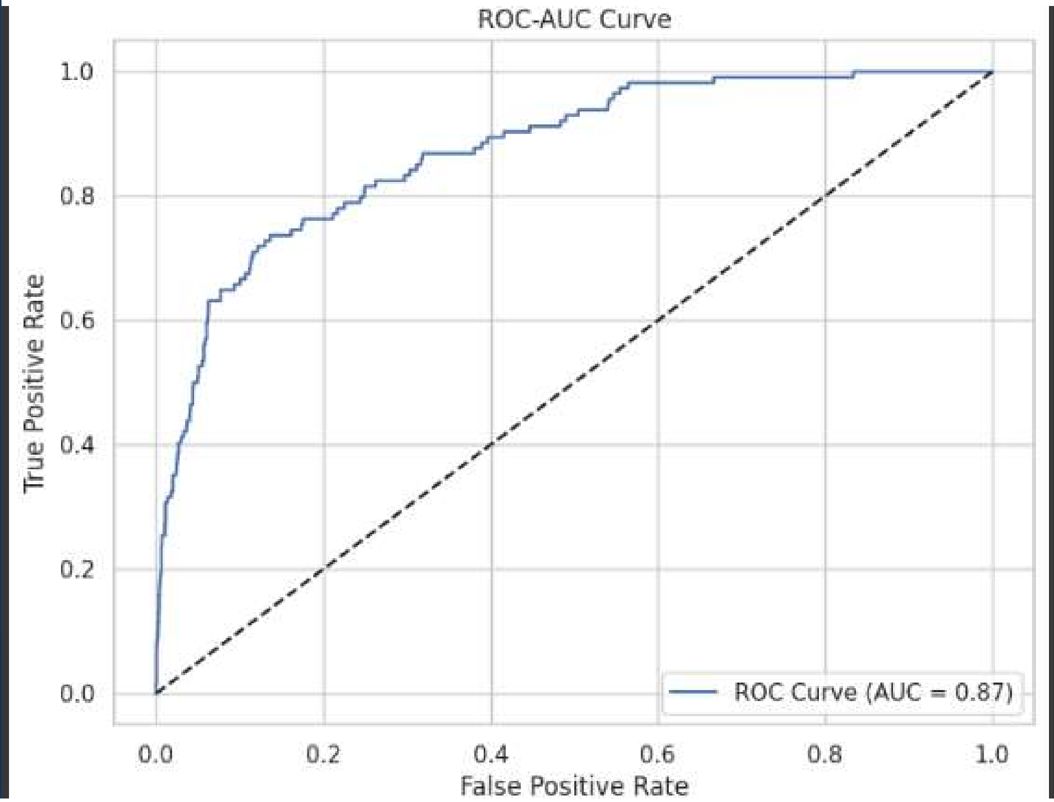
- LSTM had high training accuracy, but overfitted.
- Struggled to generalize unseen tweets (validation score dropped).

LOGISTIC REGRESSION

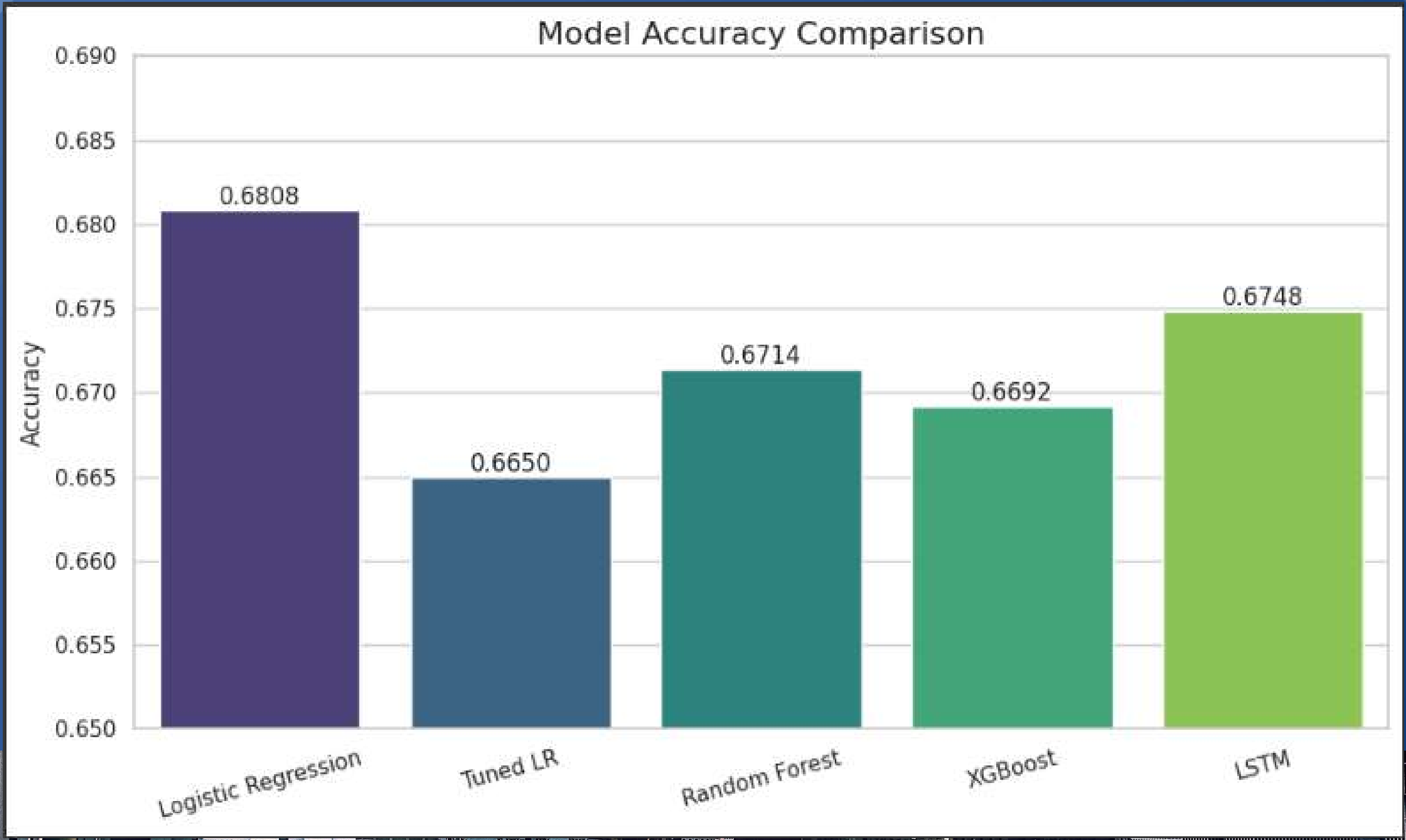
The Reliable Worker

- An AUC of 0.87 suggests that the model is performing well and can effectively classify new, unseen data with a good degree of accuracy.
- The ROC curve's upward bow toward the top-left corner shows strong classifier performance.

- Achieved 67% accuracy.
- Balanced F1-Score of 0.42.
- Best model for performance AND interpretability.



MODEL COMPARISON



MODEL COMPARISON

Our final recommendation is to use the **Logistic Regression model with tuned hyperparameters and TF-IDF features**. It consistently offers the best trade-off between **interpretability, performance, and robustness**.

Logistic Regression (Tuned):
Achieved an accuracy of **67.0%** with an improved **F1-Macro Score of 0.42**, highlighting a better **balance across all sentiment classes**.
This model was tuned after evaluating baseline models and was selected due to its strong balance of simplicity and performance.

- **LSTM (Untuned)**:
Reached a **68.4% validation accuracy**, outperforming the tuned version in generalization.
Despite being untuned, it demonstrated strong potential due to its **contextual learning capabilities**, especially with sequential data.

- **LSTM (Tuned)**:
Although hyperparameter tuning significantly boosted **training accuracy to 91.8%**, it introduced **severe overfitting —** with validation loss increasing and performance dropping after Epoch 3.
We opted for the untuned LSTM in our reporting due to better real-world generalization.

BUSINESS INSIGHTS

01 Sentiment Monitoring: Brands can track real-time reactions.

02 Marketing Optimization: Tailor campaigns based on customer emotion.

03 Reputation Management: Spot and respond to negative sentiment early.

FINAL TAKEAWAYS

Machine learning can understand real human feelings from tweets.

Logistic Regression outperformed deeper models when tuned.

Word patterns tell us a lot about customer satisfaction.

There's room to improve with better class balance and deep learning tuning.

THANK YOU